Deep Reinforcement learning-based Network slicing

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DEEP REINFORCEMENT LEARNING-BASED NETWORK SLICING

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Inria – Nokia Bell Labs common lab research action
« Analytics and machine learning for dynamic management of mobile virtualised network and service optimisation »

TEAM WORKING ON SERVICE PLACEMENT

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PLAN

- Introduction
- Challenges related to network slicing
- On using Deep Reinfocement Learning for network slicing
- Conclusions

KEY CONCERNS FOR NETWORK OPERATORS

The ability to support current, emerging and future services

- **Examples:** Automotive, mMTC, IoT/Factory automation, e-health

Ability to lease infrastructure to third parties without compromising the network and its efficiency

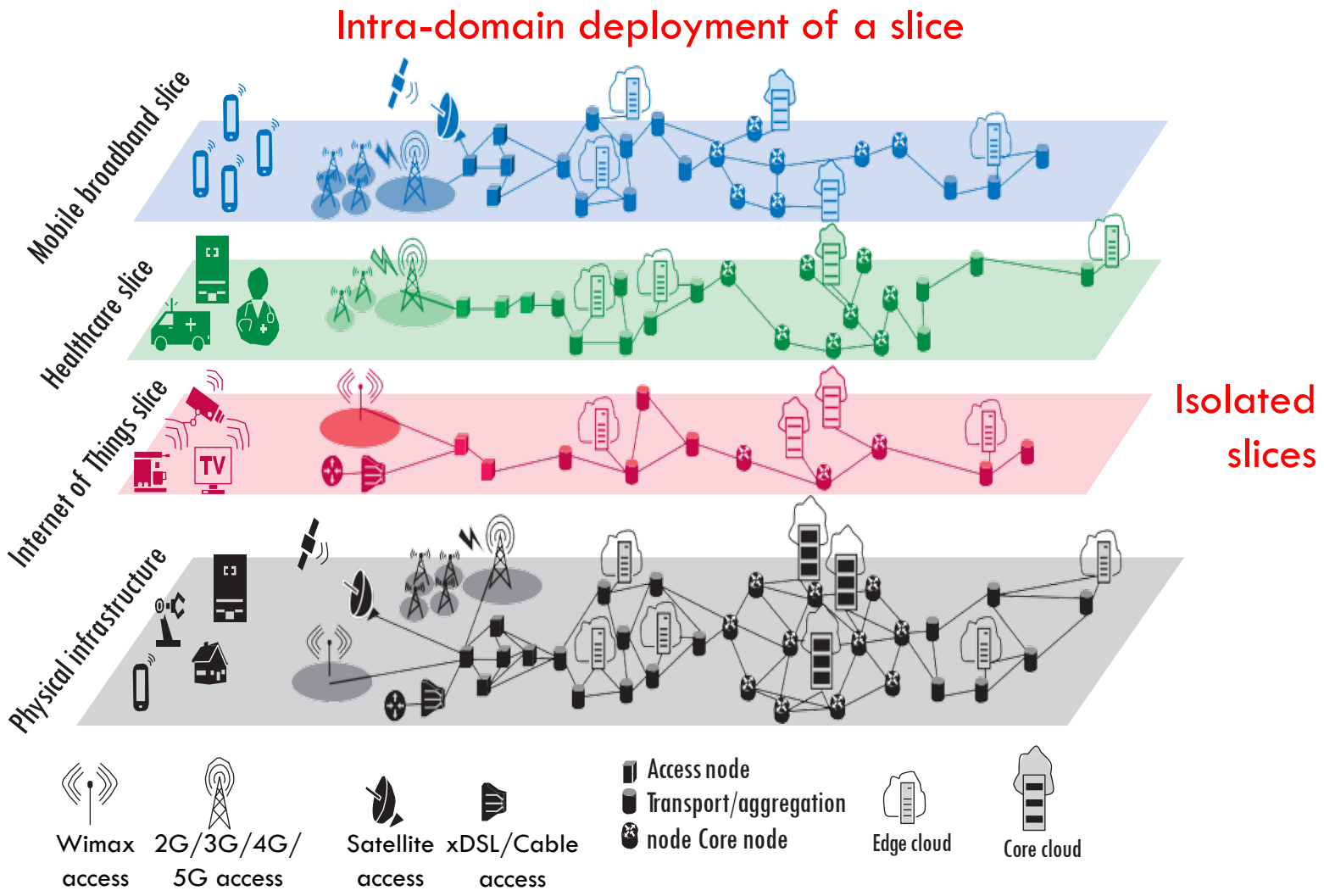
- **Consequence:** Multiple stakeholders in a network

Automation is big deal for Network Operators

- **Objective:** Zero touch networks

WHY ARE OPERATORS INTERESTED IN NETWORK SLICING?

Network slicing is seen as one of the most important technologies to meet Network Operators' expectations



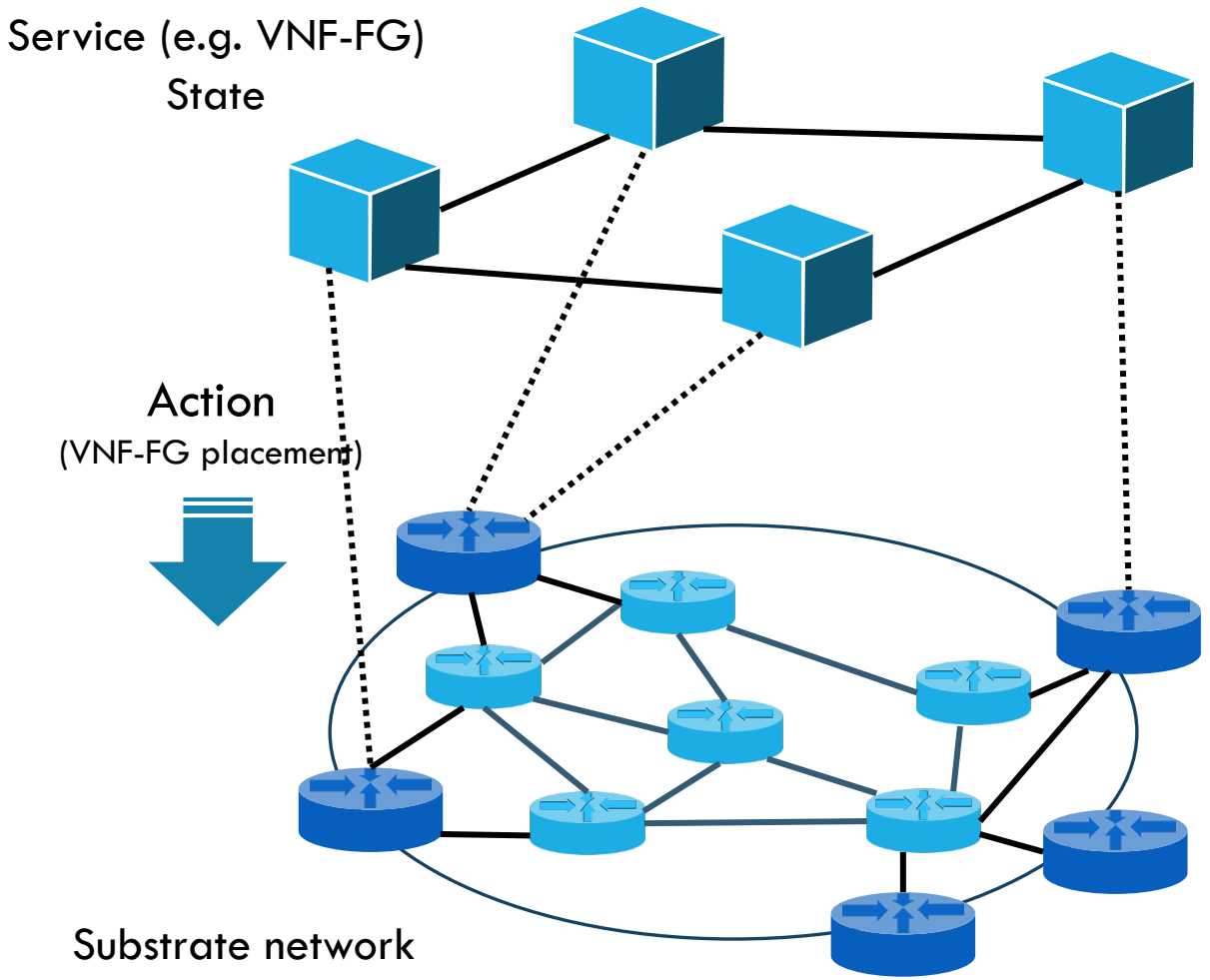
IN PRACTICE, WHAT DOES SLICING A NETWORK CONSIST OF?

Placement of services in a VNF-FG form

- Involves not only the placement of VNFs but also addressing a routing problem
  - Addressing the VNFs placement then the routing … or simultanuously
- Need to consider several metrics (QoS requirements)
- Intra-domain or multi-domain placement

Extremely large number of possibilities of placement (very large action space)

- Difficulty in finding an optimal placement, excepting for very small instances (i.e. NP-hard problem)



LIMITS OF EXISTING WORK

- Optimization problems (i.e. MILP) have the limitation of not always being applicable in a real context, given the latency of resolution or unsuitability in a real context
- Meta-heuristics are slow, require a realistic simulation environment … and there is no learning
- Heuristics are very fast but present some difficulties in finding good solutions (i.e. stuck on local minimums)
- AI-based approaches: as learning progresses, performance becomes more and more important.
  - Safety problem

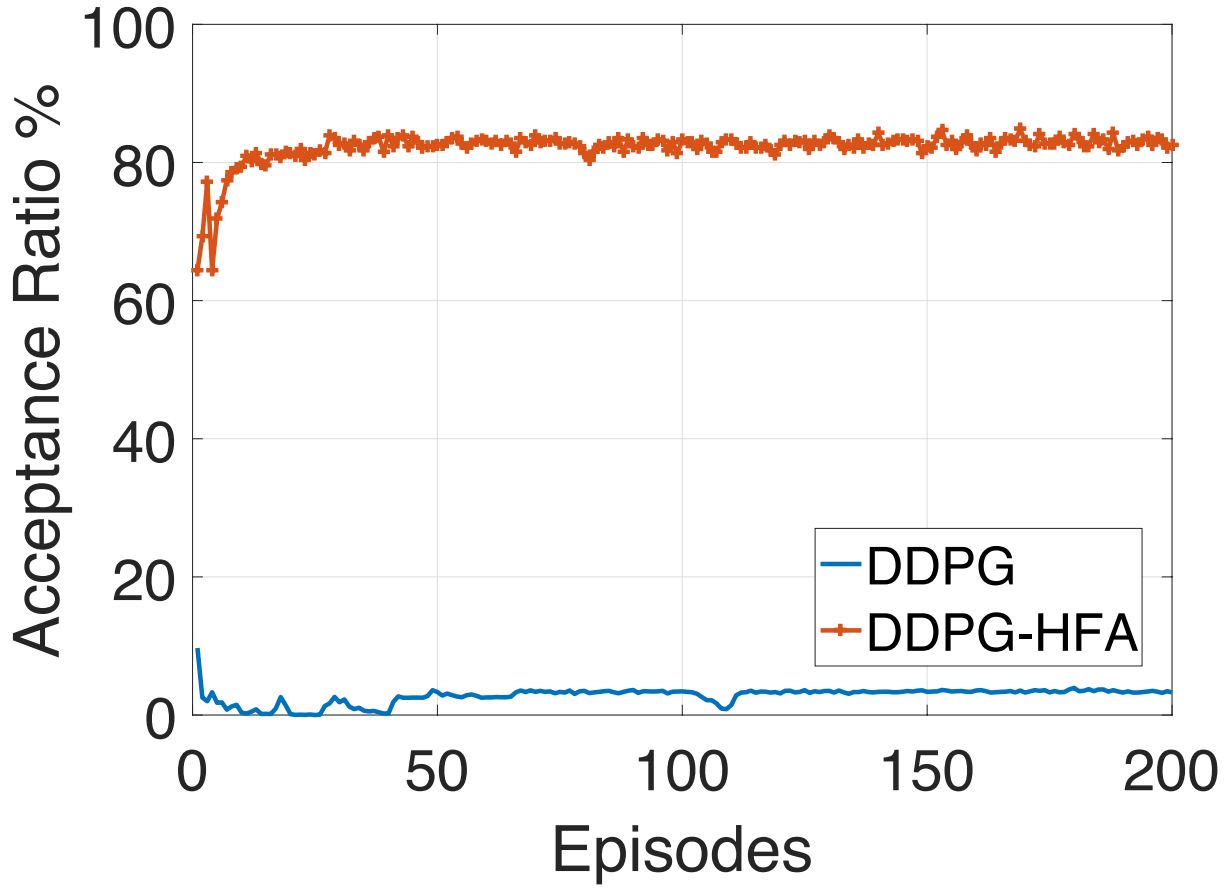
Objective

Exploring the potential of deep learning for safe placement of VNF-FG

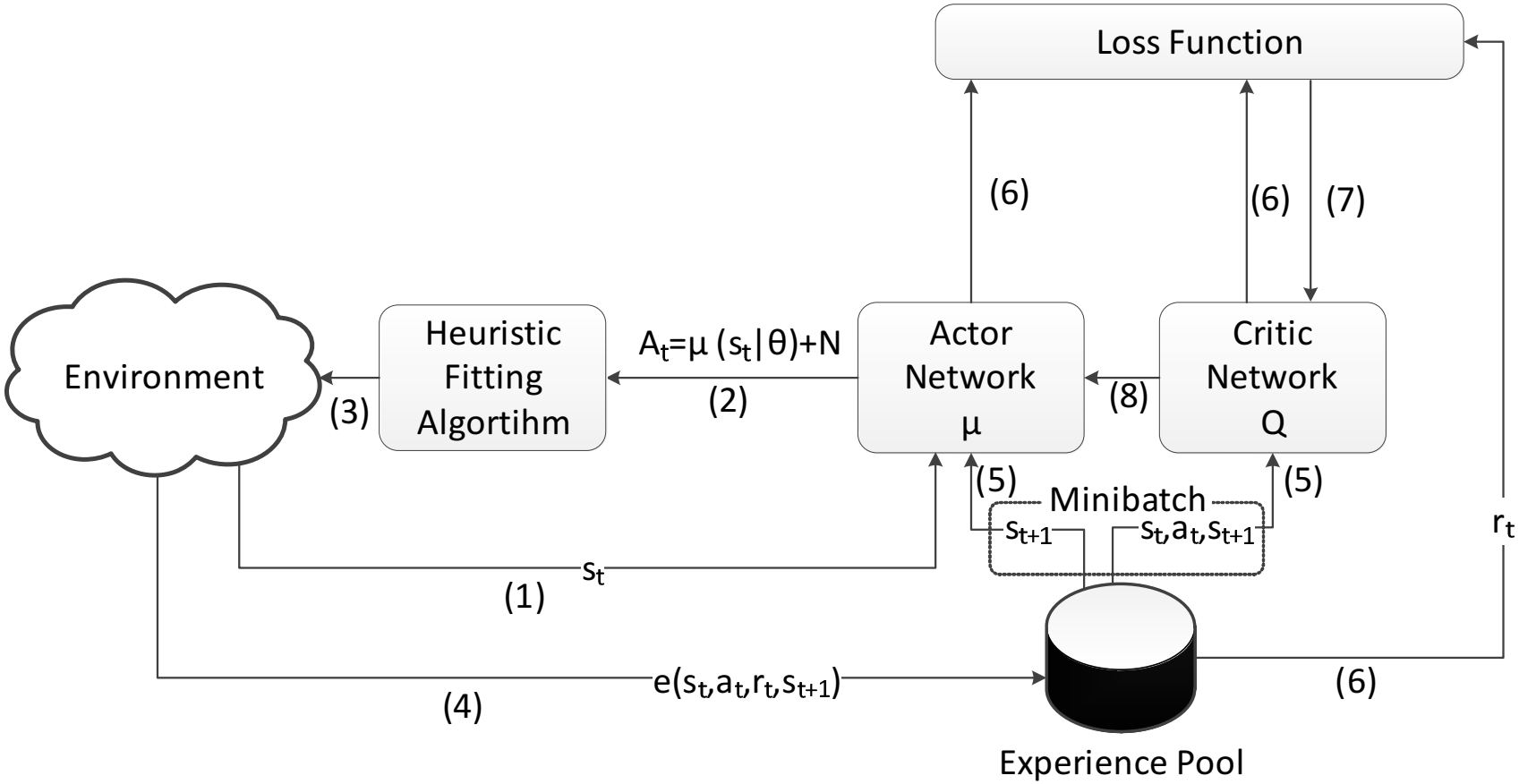
APPLICATION OF DRL FOR VNF-FG PLACEMENT

- The vanilla DDPG is not suitable for very large-scale discrete action space
- In VNF-FG embedding problem, there are constraints of resources such that some discrete actions are not feasible

Proposing to add to DDPG a Heuristic Fitting Algorithm (HFA)



DDPG-HFA


Loss Function
(6)
(6)
(7)
Environment
(3)
Heuristic Fitting Algortihm
$A_t=\mu(s_t|\theta)+N$
(2)
Actor Network μ
(8)
Critic Network Q
(5)
Minibatch
s_{t+1}
s_t,a_t,s_{t+1}
(5)
r_t
s_t
(1)
$e(s_t,a_t,r_t,s_{t+1})$
(4)
(6)
Experience Pool

ADVANTAGE

FFPG-HFA allows improving the reward

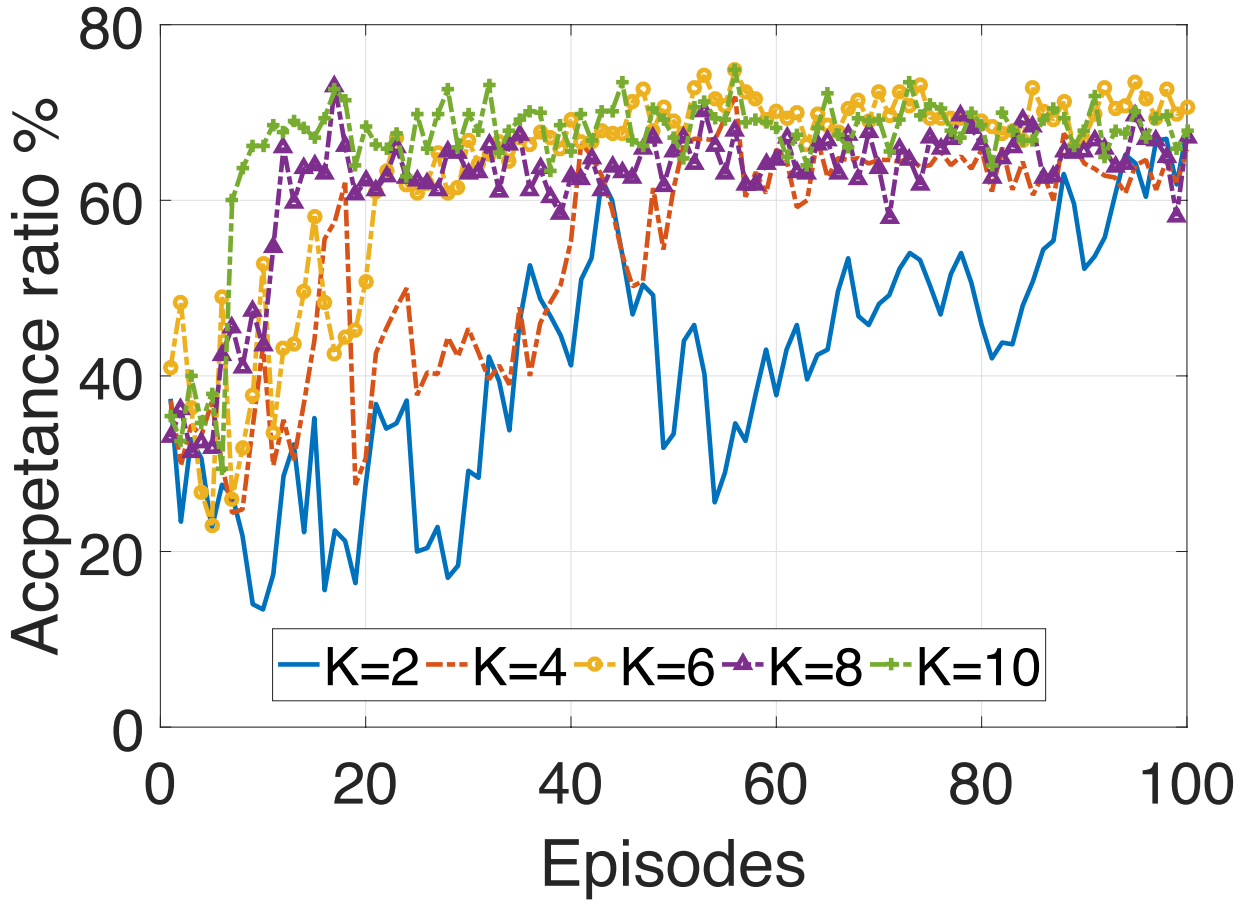
- Convergence to classical heuristic performance is immediate
  - No random behavior at the begining of the learning

Learning is slow, but once learned, execution is immediate

The proposed solution allows

- Improves the heuristic performance
- Makes the placement safer …

WHY GO DEEP?



Impact of the number of fully connected Layers

IMPROVING EXPLORATION WITH EEDDPG

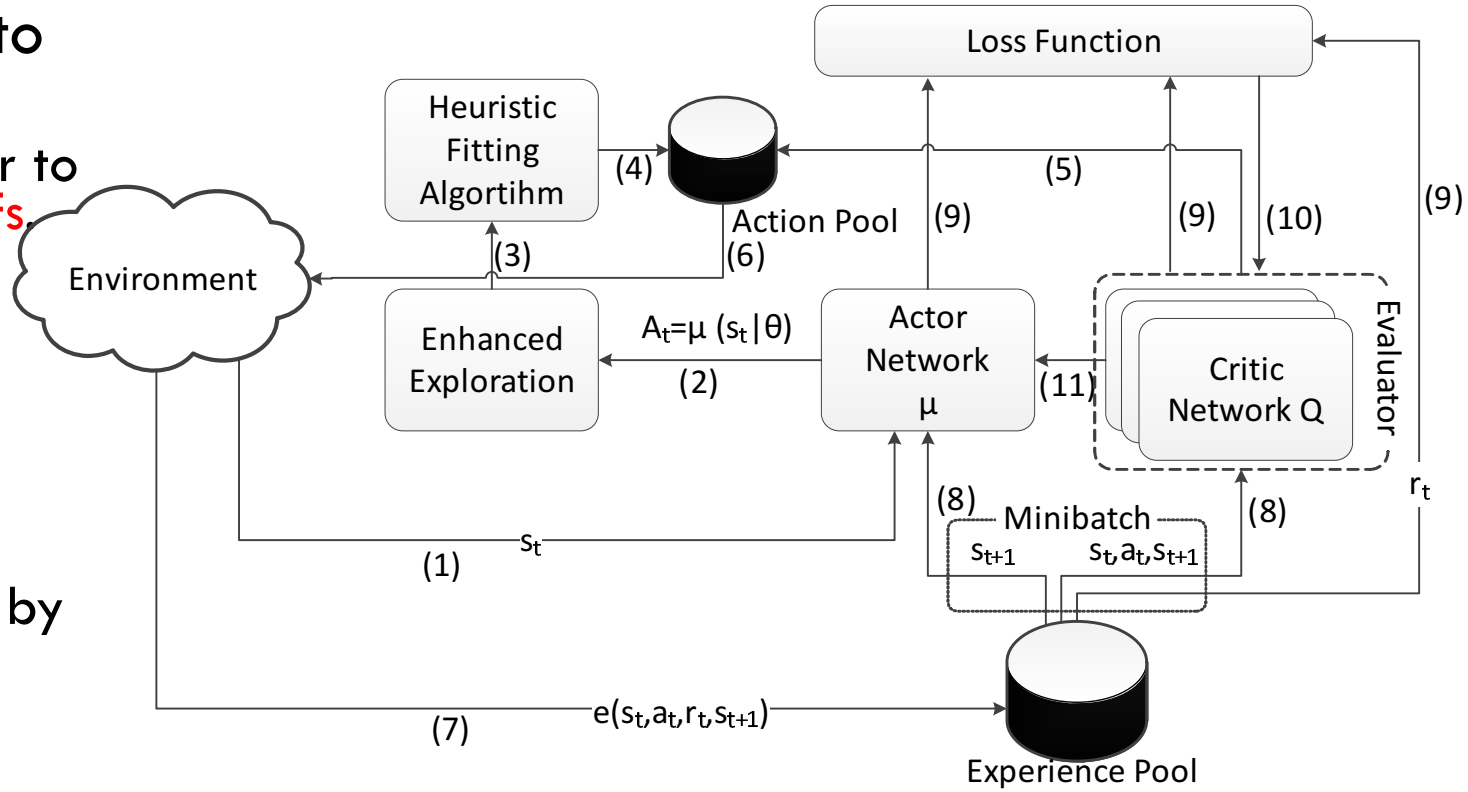
- **Noise** is added to the proto-action to create H noisy actions.
  - Each proto action is fed into HFA in order to determine the feasible allocation of VNFs.

Evaluation:

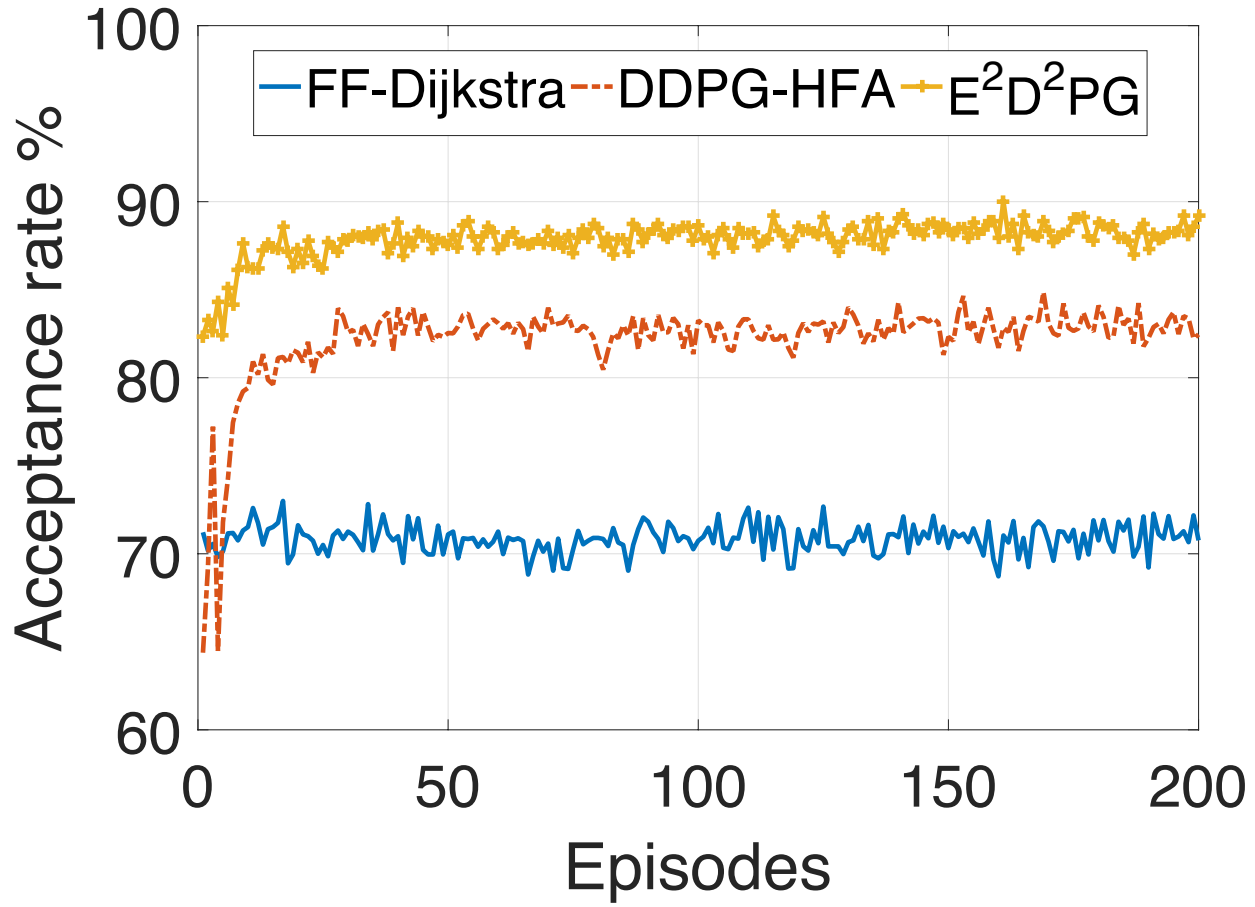
- **Multi-critic**
  - Different nets due to the arbitrary initialization
  - The best action identified (best Q value) by the evaluator will be executed

Updates of actor:

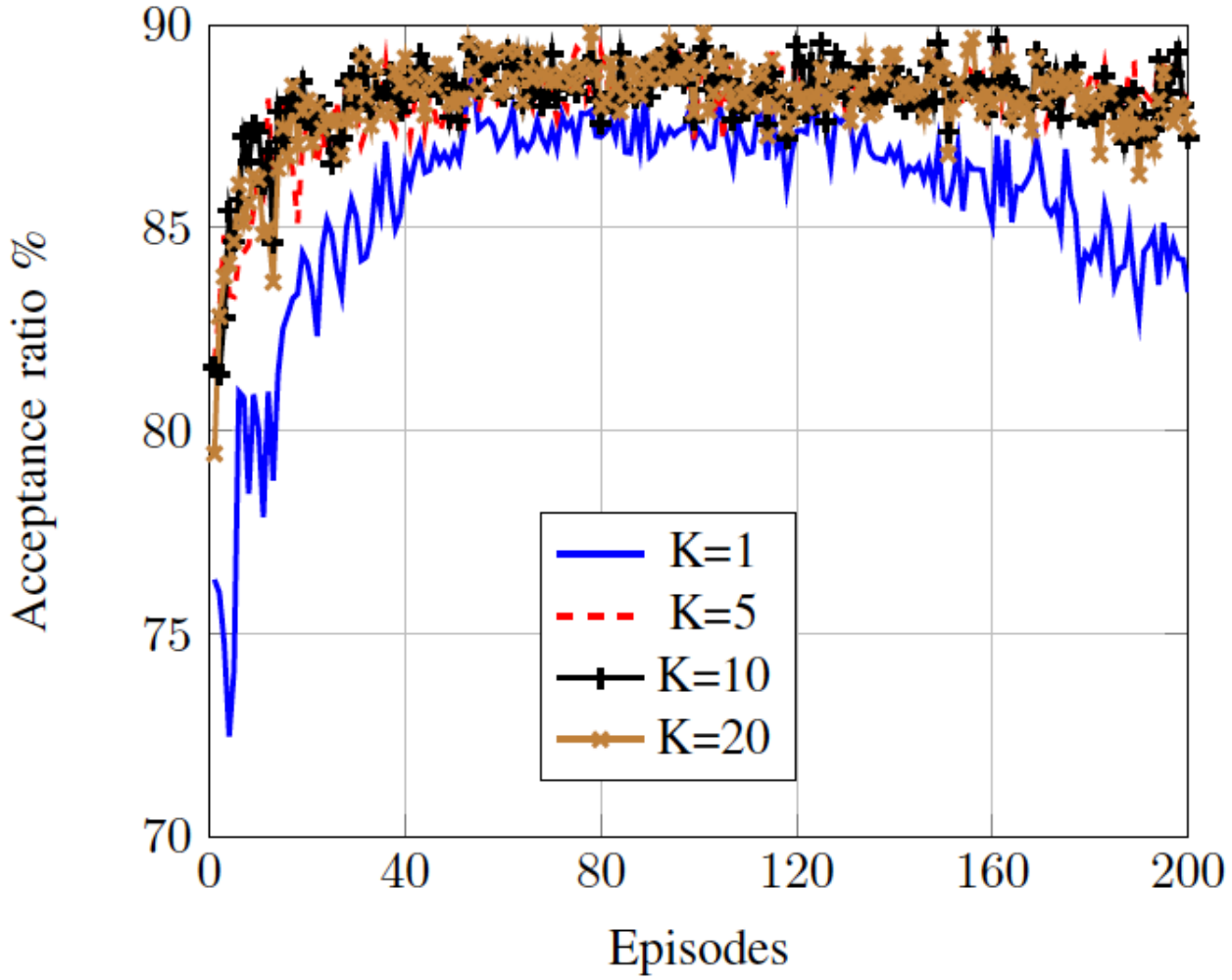
- Best critic network



RESULTS ON THE APPLICATION OF EEDDPG



IMPACT OF THE NUMBER OF CRITIC NETS



ADVANTAGE

Improving exploration allows to discover better action

- which is very efficient in congested systems

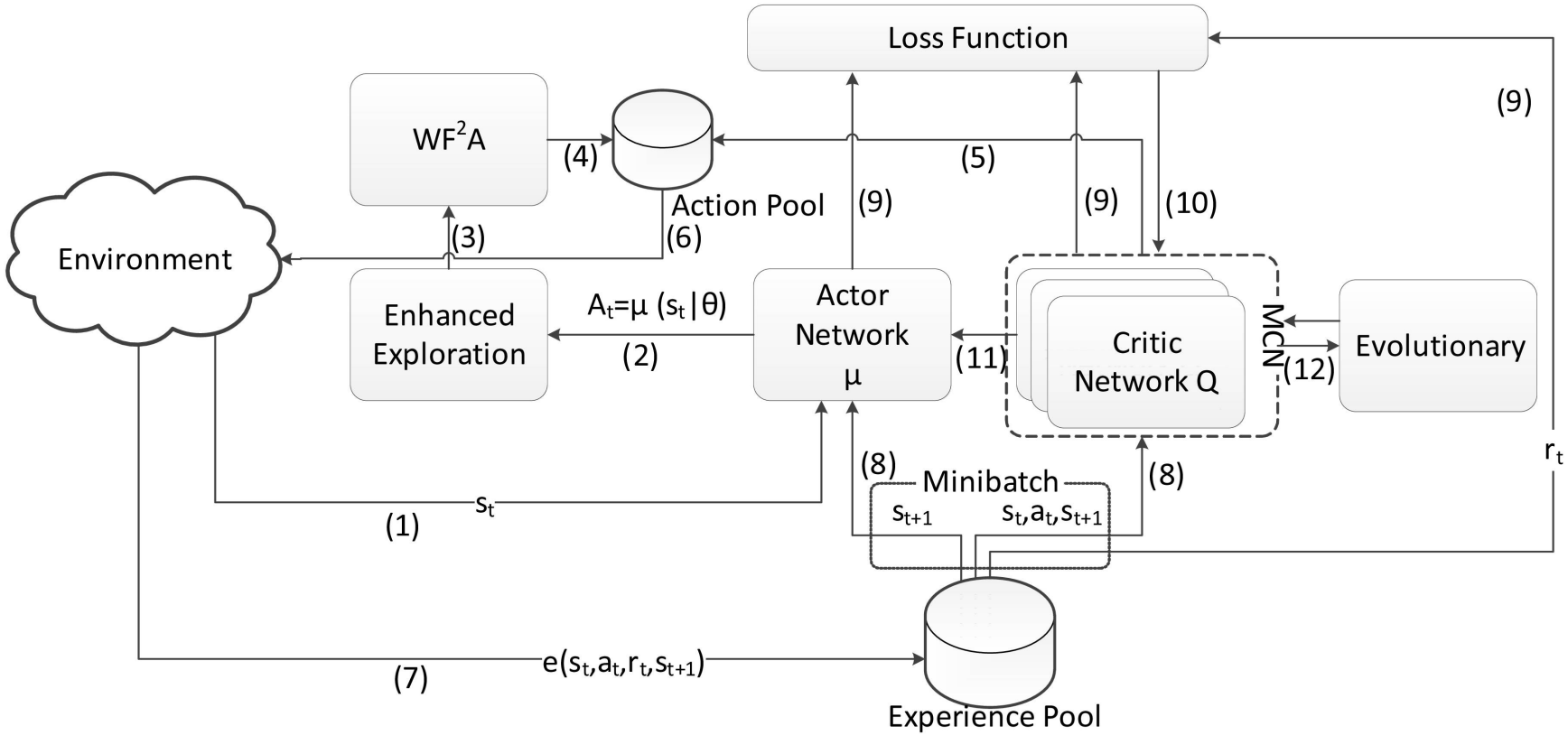
With learning techniques, there is sometimes a degradation of performance

- the use of several CRITIC networks brings more stability

The complexity is not necessarily much more important

- the back-propagation is only applied on one CRITIC network, the best ranked one

EVOLUTIONARY EEDDPG



WF²A: Weighted First Fit Algorithm – WF2A

ADVANTAGE

Discover new and much more interesting states/actions

- Effective in highly congested systems

CONCLUSIONS

DRL are very efficient in addressing the targeted issue

Lack of explainability

- But combining a heuristic with DRL allows having some guarantees in the placement quality

Efforts are still needed …

- Ongoing work on using Graph neural nets for services placement
- Combining control theory and DRL for safer placement strategies.

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